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EXAMINER	
COUGHLAN, PETER D	

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2129	

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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Office Action Summary	Application No.	Applicant(s)	
	10/542,208	BUSCEMA, MASSIMO	
	Examiner	Art Unit	
	PETER COUGHLAN	2129	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE _3_ MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on _18 November 2008_.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) _1 and 3-35_ is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) _1 and 3-35_ is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on _14 July 2005_ is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☐ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application
6) ☐ Other: _____.

Detailed Action

1. This office action is in response to an AMENDMENT entered November 18, 2008 for the patent application 10/542208 filed on July 14, 2005.

2. All previous Office Actions are fully incorporated into this Non-Final Office Action by reference.

3. Examiner's Comment: Although, the terms 'carrier wave' or 'carrier signal' is not specifically mentioned within the specification, the Examiner will exclude these interpretations wherein the context of 'media' is disclosed.

Status of Claims

4. Claims 1, 3-35 are pending.

35 USC § 101

5. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

Claims 1, 3-35 are rejected under 35 U.S.C. 101 for nonstatutory subject matter. The computer system must set forth a practical application of that § 101

judicial exception to produce a real-world result. Benson, 409 U.S. at 71-72, 175 USPQ at 676-77. The invention is ineligible because it has not been limited to a substantial practical application and/or a tangible results. The method described in claim 1 provides no practical application and no tangible result and lacks concreteness.

> [In Abele], we held unpatentable a broad independent claim reciting a process of graphically displaying variances of data from average values. *Abele*, 684 F.2d at 909. **That claim did not specify any particular type or nature of data; nor did it specify how or from where the data was obtained or what the data represented**. *Id.*; … In contrast, we held one of Abele's dependent claims to be drawn to patent-eligible subject matter where it specified that "said data is X-ray attenuation data produced in a two dimensional field by a computed tomography scanner." *Abele*, 684 F.2d at 908-09. This data clearly represented physical and tangible objects, namely the structure of bones, organs, and other body tissues. Thus, the transformation of that raw data into a particular visual depiction of a physical object on a display was sufficient to render that more narrowly-claimed process patent-eligible.
>
> … So long as the claimed process is limited to a practical application of a fundamental principle to transform **specific** data, and the claim is limited to a **visual depiction that represents specific physical objects or substances**, there is no danger that the scope of the claim would wholly pre-empt all uses of the principle.
>
> This court and our predecessor court have frequently stated that adding a data-gathering step to an algorithm is insufficient to convert that algorithm into a patent-eligible process. *E.g.*, *Grams*, 888 F.2d at 840 (step of "deriv[ing] data for the algorithm will not render the claim statutory"); *Meyer*, 688 F.2d at 794 ("[data-gathering] step[s] cannot make an otherwise nonstatutory claim statutory"). … **A requirement simply that data inputs be gathered—without specifying how—is a meaningless limit** on a claim to an algorithm because every algorithm inherently requires the gathering of data inputs. *Grams*, 888 F.2d at 839-40. Further, the inherent step of gathering data can also fairly be characterized as **insignificant extra-solution activity**. *See Flook*, 437 U.S. at 590. (See In re Bilski, 88 USPQ2d 1397-1398, emphasis added)

In determining whether the claim is for a "practical application," the focus is not on whether the steps taken to achieve a particular result are useful, tangible and concrete, but rather that the final result achieved by the claimed invention is "useful, tangible and concrete." If the claim is directed to a practical application of the § 101 judicial exception producing a result tied to the physical world that does not preempt the judicial exception, then the claim meets the statutory requirement of 35 U.S.C. § 101.

There is no practical application described within claim 1. There are no tangible results by either a direct statement or inherent within the language of the claim. The use of random distribution or pseudorandom distribution allows lack of concreteness.

The invention must be for a practical application and either:

1) specify transforming (physical thing) or

2) have the FINAL RESULT (not the steps) achieve or produce a

useful (specific, substantial, AND credible),

concrete (substantially repeatable/ non-unpredictable), AND

tangible (real world/ non-abstract) result.

A claim that is so broad that it reads on both statutory and non-statutory subject matter, must be amended.

However, the portions of the opinions in State Street and AT&T relying solely on a "useful, concrete and tangible" result analysis *should no longer be relied on*. Ex parte Bilski, Appeal No. 2007-1130 (Fed. Cir. October 30, 2008.

The court has said that there's a two-pronged test to determine whether a software of business method process patent is valid: (1) it is tied to a particular

machine or apparatus, or (2) it transforms a particular article into a different state or thing. In other words, pure software or business method patents that are neither tied to a specific machine nor change something into a different state are not patentable. Ex parte Bilski, Appeal No. 2007-1130 (Fed. Cir. October 30, 2008).

Claims that recites a method which describe the use of evolutionary algorithms to aid the training of neural networks are non-statutory. Claims that fail to produce a practical application are non-statutory. Claims that fail to produce tangible results are non-statutory. Claims that lack concreteness are non-statutory. There must be a result that has a practical application, tangible results and have concreteness.

Claim Rejections - 35 USC § 112

The following is a quotation of the second paragraph of 35 U.S.C. 112:

> The specification shall conclude with one or more claims particularly pointing out and distinctly claiming the subject matter which the applicant regards as his invention.

The term "pseudorandom" in claims 1, 33 and 35 is a relative term which renders the claim indefinite. The term "pseudorandom" is not defined by the claim, the specification does not provide a standard for ascertaining the requisite degree, and one of ordinary skill in the art would not be reasonably apprised of the scope of the invention. Although, the term itself is mentioned within the specification, there lacks an algorithm, method or guidelines which instruct how to generate ‘pseudorandom.’

These claims must be amended or withdrawn from consideration.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 1-9, 11-13, 23-25, 30-35 are rejected under 35 U.S.C. 103(a) as being unpatentable over Buscema in view of Feldgajer. ('Scientific Background of Dynamic Adaptive Systems, referred to as **Buscema**; U. S. Patent 5832466, referred to as **Feldgajer**)

Claim 1

Buscema teaches defining a set of one or more distributions of the database records onto respective training and testing subsets (**Buscema,** p2, c2:16-34; 'Training subset' of applicant is equivalent to 'training set' of Buscema. 'Testing subset' of applicant is equivalent to 'testing set' of Buscema.); using the defined set of distributions to train and test a first generation set of one or more

prediction algorithms and assigning a fitness score to each, each of said prediction algorithms being associated with a certain distribution of said database records. (**Buscema,** p3, C2:11-223; ‘Train’ of applicant is equivalent to ‘training the ANN’ of Buscema. ‘Test’ of applicant is equivalent to ‘evaluating’ of Buscema.)

Buscema does not teach feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each; continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs and wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, or a certain number of generations having been generated selecting a prediction algorithm having a best fitness score.

Feldgajer teaches feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each (**Feldgajer,** abstract, C4:43-64; ‘Feeding the set of prediction algorithms to an evolutionary algorithm’ of applicant is equivalent to ‘using genetic algorithms’ which generate ‘parameter values preferably define a first broad range of values’ of Feldgajer. ‘Fitness score’ of applicant is illustrates by finding output with the ‘best fit’ of Feldgajer.); continuing to feed each generational set of prediction algorithms to the

evolutionary algorithm until a termination event occurs (**Feldgajer,** abstract, C4:43-64; 'Continuing to feed each generational set of prediction algorithms' of applicant is disclosed by 'new parameters values are assigned to the plurality of groups' of Feldgajer.) and wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value(**Feldgajer,** C2:1-26; 'Exceeding a defined minimum' of applicant is disclosed by the neuron and its 'internal potential limit' of Feldgajer. This node can be viewed as the output node of the neural network. The node will fire if the .minimum value' is equaled or exceeded.), the maximum fitness score of successive generational sets of prediction algorithms converging to a given value (**Feldgajer,** C5:63-64; 'Converging to a given value' of applicant is illustrated by the method of employing 'a convergent result.' Of Feldgajer.) , or a certain number of generations having been generated (**Feldgajer,** C7:50 through C8:17; 'Certain number of generations' of applicant is equivalent to generation counter' of Feldgajer.) selecting a prediction algorithm having a best fitness score. (**Feldgajer**, C4:43-64; 'Fitness score' of applicant is illustrates by finding output with the 'best fit' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using the iterations of a genetic algorithm to modify the neural networks as taught by Feldgajer to feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each; continuing to feed each generational set of prediction algorithms to the evolutionary

algorithm until a termination event occurs and wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, or a certain number of generations having been generated selecting a prediction algorithm having a best fitness score.

For the purpose of speeding up the training time, thus reducing the cost.

Buscema teaches using the distribution of database records associated with said selected prediction algorithm in performing supervised learning, said supervised learning including training and testing of prediction algorithms to obtain a trained prediction algorithm. (**Buscema,** p4, Figure 4; 'Using the distribution of database records' of applicant is equivalent to 'Total DB' of Buscema.)

Buscema does not teach wherein said method is performed using a computer and computer software forming an intelligent system.

Feldgajer teaches wherein said method is performed using a computer and computer software forming an intelligent system. (**Feldgajer**, C4:43-64; 'Computer and computer software' of applicant is equivalent to 'computer' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using a computer as taught by Feldgajer to wherein said method is performed using a computer and computer software forming an intelligent system.

For the purpose of implementing the invention on current hardware for ease of implementation.

Buscema teaches the trained prediction algorithm is effective to predict output variables for data relating to said condition, thereby predicting diagnosis of said condition. (**Buscema,** p2:16-34) the method further comprises the steps of generating a population of prediction algorithms, wherein each one of said prediction algorithms is trained and tested according to a different distribution of the records of the data set in the complete database onto a training data set and a testing data set (**Buscema**, p4 Figure 4, p2 C2:16-39; ‘population of prediction algorithms ‘of applicant is illustrated by ANN1 through ANNn of Buscema. ‘Training data’ of applicant is equivalent to ‘training set’ of Buscema. ‘Tested data set’ of applicant is equivalent to ‘testing set’ of Buscema.)

Buscema does not teach each different distribution being created as one or more of a random distribution or a pseudorandom distribution

Feldgajer teaches each different distribution being created as one or more of a random distribution or a pseudorandom distribution (**Feldgajer,** C7:50 through C8:17; ‘Random’ of applicant is equivalent to ‘random’ of Feldgajer. ‘Pseudorandom’ of applicant is equivalent to ‘pseudorandom’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using random and pseudorandom distributions as taught by Feldgajer to each different distribution being created as one or more of a random distribution or a pseudorandom distribution

For the purpose of getting a true sample for training purposes

Buscema teaches each prediction algorithm of said population is trained according to its own distribution of records of the training set and being validated in a blind way according its own distribution on the testing set. (**Buscema**, p4 Figure 4; 'Trained according to its own distribution' and 'validated in a blind way according its own distribution' of applicant is illustrated in the 'training side' and 'validation side' of each ANN of Buscema.)

Buscema does not teach a score reached by each prediction algorithm is calculated in the testing phase representing its fitness an evolutionary algorithm being.

Feldgajer teaches a score reached by each prediction algorithm is calculated in the testing phase representing its fitness (**Feldgajer,** C4:43-64; If Feldgajer can determine which parameter is the 'best fit' then a 'score' must be generated.) an evolutionary algorithm being (**Feldgajer,** abstract; 'Evolution algorithm' of applicant is equivalent to 'genetic algorithm' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using a score to rate performance as taught by Feldgajer to have a score reached by each prediction algorithm is calculated in the testing phase representing its fitness an evolutionary algorithm being.

For the purpose of using the score for future selection.

Buscema teaches further provided which combines the different models of distribution of the records of the complete data set in a training and in a testing

set which sets are represented each one by a corresponding prediction algorithm trained and tested on the basis of the said training and testing data set according to the fitness score calculated in the previous step for the corresponding prediction algorithm (**Buscema**, p4 Figure 4; ‘Training set’ and ‘testing set’ of applicant is equivalent to ‘training’ and ‘validation’ of Buscema. Examiner’s Comment: Feldgajer discloses a method is disclosed that, using genetic algorithms, improves the training characteristics of a neural network. This is used in combination with Buscema that picks both training and testing records from a database. How these training and testing records are picked is disclosed by 'improves the training characteristics of a neural network.')

Buscema does not teach the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

Feldgajer teaches the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the

training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets (**Feldgajer,** C4:43-64; If Feldgajer can determine which parameter is the ‘best fit’ then a ‘score’ must be generated.) repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value (**Feldgajer,** C7:50 through C8:17; ‘Repeating the evolution’ of applicant is equivalent to ‘performed iteratively’ of Feldgajer.) setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm. (**Feldgajer,** p7:50 through C8:17; ‘Setting the data records’ of applicant is equivalent to ‘altering the population or the parameter values’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by iterating the process between the genetic algorithm and neural networks to modify the neural network as taught by Feldgajer to have the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness

value of at least some prediction algorithm related to an associated data records distribution has reached a desired value setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

For the purpose of lowering the cost of training the neural network.

Claim 3.

Buscema teaches wherein to each record of the data set a distribution variable is associated which is binary and has at least two statuses, one of this two statuses being associated with the inclusion of the record in the training set and the other in the testing set. (**Buscema,** p2, c2:16-34; ‘Training subset’ of applicant is equivalent to ‘training set’ of Buscema. ‘Testing subset’ of applicant is equivalent to ‘testing set’ of Buscema.)

Claim 4

Buscema teaches wherein the prediction algorithm is an artificial neural network. (**Buscema**, p4 Figure 4; ‘ANN’ of applicant is an ‘artificial neural network’ of Buscema.)

Claim 5

Buscema teaches wherein the prediction algorithm is a classification algorithm. (**Buscema**, p4 Figure 4; ‘ANN’ of applicant is a ‘classification algorithm’ of Buscema.)

Claim 6

Buscema does not teach wherein that once an optimum distribution has been computed, the optimized training data subset is made equal to a complete data set being the individuals included in the training subset distributed onto a new training set and onto a new testing set each one having about the half of the records of the original optimized training set, while the originally optimized testing set is used as a third data subset for validation purposes.

Feldgajer teaches wherein that once an optimum distribution has been computed, the optimized training data subset is made equal to a complete data set being the individuals included in the training subset distributed onto a new training set and onto a new testing set each one having about the half of the records of the original optimized training set, while the originally optimized testing set is used as a third data subset for validation purposes. (**Feldgajer,** C4:43-64; 'Training subset distributed onto a new training set' of applicant is disclosed by the generation of a 'second range of values' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by altering the training set as taught by Feldgajer to wherein that once an optimum distribution has been computed, the optimized training data subset is made equal to a complete data set being the individuals included in the training subset distributed onto a new training set and onto a new testing set each one having about the half of the

records of the original optimized training set, while the originally optimized testing set is used as a third data subset for validation purposes.

For the purpose of improving the training time.

Claim 7

Buscema does not teach wherein the distribution of the data of the originally optimized training set onto the new training and new testing set is optimized through a pre-processing phase including the steps of said method for optimizing a database of sample records, said records being records in the originally optimized training set

Feldgajer teaches wherein the distribution of the data of the originally optimized training set onto the new training and new testing set is optimized through a pre-processing phase (**Feldgajer,** ‘Preprocessing phase’ of applicant is the ‘genetic algorithm’ of Feldgajer.) including the steps of said method for optimizing a database of sample records, said records being records in the originally optimized training set (**Feldgajer,** C10:16-26; ‘Optimizing a database’ of applicant is equivalent to ‘method using groups’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by having wherein the distribution of the data of the originally optimized training set onto the new training and new testing set is optimized through a pre-processing phase including the steps of said method for optimizing a database of sample records, said records being records in the originally optimized training set

For the purpose of resulting in a preprocessed distribution of data.

Claim 8

Buscema teaches wherein the different choices of the structure of the training subset and the structure of the testing subset consist in different selections of the number of input variables of the data records of the database, which selections consist in leaving out at least one, variable from the entire input variable set forming each record, the records of the database data base comprising a certain number of known input variables and a certain number of known output variables. (**Buscema**, p4 Figure 4; 'Different choices of structures' of applicant is equivalent to all of the different neural networks, ANN1 through ANNn of Buscema.)

Claim 9

Buscema teaches defining a distribution of data from the complete data set onto a training data set and onto a testing data set (**Buscema,** p2, c2:16-34; 'Training subset' of applicant is equivalent to 'training set' of Buscema. 'Testing subset' of applicant is equivalent to 'testing set' of Buscema.); generating a population of different prediction algorithm each one having a training and/or testing data set in which only some variables have been considered among all the original variables provided in the data sets, each one of the prediction algorithms being generated through a different selection of variables

(**Buscema**, p4 Figure 4; 'Generating a population of different prediction algorithm' of applicant is equivalent to all of the different neural networks, ANN1 through ANNn of Buscema.) carrying out learning and testing of each prediction algorithm of the population and evaluating the fitness score of each prediction algorithm. (**Buscema**, p4 Figure 4; 'Learning' of applicant is equivalent to 'training' of Buscema. 'Evaluation' of applicant is equivalent to 'validation' of Buscema.)

Buscema does not teach applying an evolutionary algorithm to the population of prediction algorithms for achieving new generations of prediction algorithm for each generation of new prediction algorithms representing each one a new different selection of input variable, testing or validating the best prediction algorithm according to the best hypothesis of input variables selection and evaluating a fitness score and promoting the prediction algorithms representing the selections of input variables which have the best testing performances and the minimum input variables for the processing of the new generations.

Feldgajer teaches applying an evolutionary algorithm to the population of prediction algorithms for achieving new generations of prediction algorithm (**Feldgajer,** C6:1-4; 'Applying an evolution algorithm' of applicant is equivalent to using a genetic algorithm to evolve the learning parameters of the neural network.) for each generation of new prediction algorithms representing each one a new different selection of input variable, testing or validating the best prediction algorithm according to the best hypothesis of

input variables selection (**Feldgajer,** Fig 4, abstract; ‘Testing or validating’ of applicant is inherent by ‘each generation based on the network with the best training response in the previous generation’ of Feldgajer. ‘New different selection of input variable’ of applicant is equivalent to ‘modify population of individual neural networks’ of Feldgajer.) and evaluating a fitness score and promoting the prediction algorithms representing the selections of input variables which have the best testing performances and the minimum input variables for the processing of the new generations. (**Feldgajer,** C4:43-64, abstract; ‘Fitness score’ of applicant is illustrates by finding output with the ‘best fit’ of Feldgajer. Evaluating a fitness score and promoting’ of applicant is inherent to ‘each generation based on the network with the best training response in the previous generation’ of Feldgajer) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by applying an evolutionary algorithm to the population of prediction algorithms for achieving new generations of prediction algorithm for each generation of new prediction algorithms representing each one a new different selection of input variable, testing or validating the best prediction algorithm according to the best hypothesis of input variables selection and evaluating a fitness score and promoting the prediction algorithms representing the selections of input variables which have the best testing performances and the minimum input variables for the processing of the new generations.

For the purpose of employing these values to alter a neural network.

Claim 11

Buscema does not teach wherein different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database, which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables, and further comprising a pre-processing phase, including the steps of said method for optimizing a database of sample records, for selecting the most predictive input variables, wherein the database subjected to the a pre-processing phase of input variable selection is a training subset and a testing subset processed with said method.

Feldgajer teaches wherein different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database, which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables (**Feldgajer,** C7:34 through C8:17; ‘Minimum number of selected input variables’ of applicant is illustrated by a genetic algorithm is used to ‘reduce the amount of information required to generate an adequate result’ of Feldgajer.), and further comprising a pre-processing phase, including the steps of said

method for optimizing a database of sample records, for selecting the most predictive input variables, wherein the database subjected to the a pre-processing phase of input variable selection is a training subset and a testing subset processed with said method. (**Feldgajer,** C10:16-26; 'Optimization of the distribution' of applicant is equivalent to 'method using groups' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by reducing the number of variables if possible as taught by Feldgajer to have wherein different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database, which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables, and further comprising a pre-processing phase, including the steps of said method for optimizing a database of sample records, for selecting the most predictive input variables, wherein the database subjected to the a pre-processing phase of input variable selection is a training subset and a testing subset processed with said method.

For the purpose of increasing the speed by removing some of the input variables of the neural network.

Claim 12

Buscema does not teach wherein the complete database the distribution of the records of which has to be optimized has data records having a selected number of input variables, the selection being carried out with said method, and in which different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database. which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables.

Feldgajer teaches wherein the complete database the distribution of the records of which has to be optimized has data records having a selected number of input variables, the selection being carried out with said method, and in which different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database. which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables. (**Feldgajer,** C7:34 through C8:17; ‘Minimum number of selected input variables’ of applicant is illustrated by a genetic algorithm is used to ‘reduce the amount of information required to generate an adequate result’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by reducing the number of input parameters as taught

by Feldgajer to have wherein the complete database the distribution of the records of which has to be optimized has data records having a selected number of input variables, the selection being carried out with said method, and in which different choices of the structure of the training subset and the structure of the testing subset comprise different selections of the number of input variables of the data records of the database. which selections comprise leaving out at least one, variable from the entire input variable set forming each record, the records of the database comprising a certain number of known input variables and a certain number of known output variables.

For the purpose of increasing the speed by removing some of the input variables of the neural network.

Claim 13

Buscema does not teach wherein a pre-processing phases for optimizing the distribution of the records on a training subset and a testing subset and for selecting the most predictive input variables, is carried out alternatively one to the other several times.

Feldgajer teaches wherein a pre-processing phases for optimizing the distribution of the records on a training subset and a testing subset and for selecting the most predictive input variables, is carried out alternatively one to the other several times. (**Feldgajer,** C10:16-26; 'Optimization of the distribution' of applicant is equivalent to 'method using groups' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's

invention to modify the teachings of Buscema by optimization the distribution as taught by Feldgajer to have wherein a pre-processing phases for optimizing the distribution of the records on a training subset and a testing subset and for selecting the most predictive input variables, is carried out alternatively one to the other several times.

For the purpose of using existing distribution data as efficiently as possible.

Claim 23

Buscema does not teach wherein the method is in the form of a software program comprising instructions executable by a CPU, the software program being stored in a memory accessible by the CPU.

Feldgajer teaches wherein the method is in the form of a software program comprising instructions executable by a CPU, the software program being stored in a memory accessible by the CPU. (**Feldgajer,** C4:43-64; ‘Instructions executable by a CPU, the software program being stored in a memory to which the CPU can access’ of applicant are all common functions of a ‘computer’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by implementing the invention on a computer as taught by Feldgajer to have wherein the method is in the form of a software program comprising

instructions executable by a CPU, the software program being stored in a memory accessible by the CPU.

For the purpose of implementing the invention on a common device to encourage its use.

Claim 24

Buscema does not teach a software program stored on a memory device, wherein the software program consisting in the method according to claim 1 in the form of executable instructions by a CPU or by a computer system.

Feldgajer teaches a software program stored on a memory device, wherein the software program consisting in the method according to claim 1 in the form of executable instructions by a CPU or by a computer system. (**Feldgajer,** C4:43-64; ‘Software program stored on a memory device, the said software program consisting in the method according to claim 1 in the form of a executable instructions of a CPU or of a computer system’ of applicant are all common functions of a ‘computer’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using standard memory with the invention as taught by Feldgajer to have a software program stored on a memory device, wherein the software program consisting in the method according to claim 1 in the form of executable instructions by a CPU or by a computer system.

For the purpose of implementing the invention on a common device to encourage its use.

Claim 25

Buscema teaches an apparatus or device for generating an action of response which is autonomously. (**Buscema,** p4, Figure 4; The contents of the ANN supervised validation protocol is a stand alone design.) chosen among a certain number of different kinds of actions of response stored in a memory of the apparatus or autonomously generated by the apparatus basing the choice of the kind of action of response on the interpretation of data collected autonomously by one or more sensors responsive to physical entities or which are fed to the apparatus of input means. (**Buscema,** p4, Figure 4, Examples of 'actions and responses' of applicant is equivalent to 'the benign and malignant tumors and their characteristics of Buscema.)

Buscema does not teach the said interpretation being made through a prediction algorithm in the form of software saved in a memory of said apparatus and being carried out by a central processing unit.

Feldgajer teaches the said interpretation being made through a prediction algorithm in the form of software saved in a memory of said apparatus and being carried out by a central processing unit. (**Feldgajer,** C4:43-64; 'Central processing unit' of applicant is an element of a 'computer' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using standard computer operations as taught by Feldgajer to have said interpretation being

made through a prediction algorithm in the form of software saved in a memory of said apparatus and being carried out by a central processing unit.

For the purpose of implementing the invention on a computer with normal operating characteristics

Buscema teaches wherein the apparatus is further provided with means for carrying out a training and testing phase of the prediction algorithm by inputting to the said prediction algorithm data of a known database in which input variables of the input data representing the physical entities being sensed by the apparatus through the one or more sensors and/or fed to the apparatus by the input means are univoquely correlated to at least one definite kind of action of response among the different kinds of possible action of response. (**Buscema,** p4, Figure 4; 'Training and testing' of applicant is equivalent to 'testing' and 'validation' of Buscema.)

Buscema does not teach the means for carrying out the training an testing being in the form of a training and testing software saved in a memory of the apparatus, the training and testing being carried out by method according to claim 1, the training and testing software program being the said method of training and testing in the form of' a software program or instructions.

Feldgajer teaches the means for carrying out the training an testing being in the form of a training and testing software saved in a memory of the apparatus, the training and testing being carried out by method according to claim 1, the training and testing software program being the said method of training and testing in the form of' a software program or instructions. (**Feldgajer,** C4:43-64;

'Carrying out the training an testing' using 'memory' of applicant are all normal operations of a 'computer' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using memory to hold testing and training software as taught by Feldgajer to have the means for carrying out the training an testing being in the form of a training and testing software saved in a memory of the apparatus, the training and testing being carried out by method according to claim 1, the training and testing software program being the said method of training and testing in the form of' a software program or instructions.

For the purpose of implementing the invention in a normal established method.

Claim 30

Buscema teaches a method for producing a microarray for genotyping operations (**Buscema,** p4, Figure 4; 'Microarray for genotyping operations' of applicant is equivalent to all the ANN 1 through n of Buscema.), the said method comprising the steps of defining a certain number of theoretically relevant genes or alleles or polymorphisms considered relevant for a certain biologic condition like a tissue structure, a pathology or the potentiality of developing a pathology or an anatomic or morphologic feature the method comprising (**Buscema,** p2:16-39; 'Relevant for a certain biologic condition' of applicant is disclosed by classifying new cases for tumors of Buscema.); providing a database of experimentally

determined data in which each record relates to a known clinical or experimental case of a sample population of cases and which records comprise a certain number of input variables corresponding to the presence/absence of a certain predetermined number of polymorphisms and/or mutations and/or equivalent genes of a certain number of theoretically probable relevant genes, said certain predetermined number of polymorphisms and/or genes forming a set, and one or more related output variables corresponding to the certain biological or pathologic condition of the clinical and experimental cases of the sample population (**Buscema,** p4, Figure 4; 'Database of experimentally determined data' of applicant is equivalent to 'Total DB' of Buscema.) determining a selection of a subset of the set of certain predetermined number of polymorphisms and/or genes by testing the association of the genes or polymorphisms and the biological or pathological condition by mathematical tools applied to the database (**Buscema,** p4, Figure 4; One example of a tool is a artificial neural network' of Buscema.); the mathematical tools comprising a so prediction algorithm (**Buscema,** p4, Figure 4; One example of a tool is a artificial neural network' of Buscema.); and the further steps are carried out of: dividing the database into a training and a testing dataset for training and testing the prediction algorithm. (**Buscema,** p4, Figure 4; Buscema discloses the database being divided into training and testing sets.)

Buscema does not teach defining two or more different training datasets each one having records with a set of input variables obtained by excluding one or more input variables from the originally defined number of input variables.

while for each record the set of input variables of the corresponding training set has at least one input variable which is not a member of the set of input variables of the other training datasets, each said at least one input variable comprising a different gene or a different polymorphism and/or a different mutation and/or a different functionally equivalent gene thereof of the originally considered genes or polymorphisms and/or mutations and/or functionally equivalent genes thereof considered theoretically potentially relevant for the biologic or pathologic condition training the prediction algorithm with each of the different training sets defined at the previous step for generating a first population of different prediction algorithms which are divided into two groups of mother and father prediction algorithms and testing the prediction algorithms with the associated testing set calculating a fitness score or prediction accuracy of each father and mother prediction algorithms of the said first population through the testing results; providing an evolutionary algorithm such as a genetic algorithm and applying the evolutionary algorithm to the first population of mother and father prediction algorithms for achieving new generation of prediction algorithms whose training and testing dataset comprises records whose input variables selections are a combination of the input variable selections of the records of the training and of the testing datasets of the first or previous population of father and mother prediction algorithms according to the rules of the evolutionary algorithm for each generation of new prediction algorithms representing each new variant selection of input variables, the best prediction algorithm according to the best hypothesis of input variable selection being tested or validated through the testing dataset;

evaluating a fitness score and the promoting prediction algorithms representing the selections of input variables which have the best testing performance with the minimum number of input variables utilized are for the processing of new generations; repeating the preceding two steps until a predetermined fitness score defined as best fit of the prediction algorithm and a minimum number of input variables has been reached; and defining as the selected relevant input variables the selected input variables comprising the relevant genes or polymorphisms and/or of mutations and/or of functionally equivalent genes thereof the ones related to the input variables of the selection represented by the prediction algorithm having both at least the predetermined fitness score and also the minimum number of selected input variables.

Feldgajer teaches defining two or more different training datasets each one having records with a set of input variables obtained by excluding one or more input variables from the originally defined number of input variables. while for each record the set of input variables of the corresponding training set has at least one input variable which is not a member of the set of input variables of the other training datasets, each said at least one input variable comprising a different gene or a different polymorphism and/or a different mutation and/or a different functionally equivalent gene thereof of the originally considered genes or polymorphisms and/or mutations and/or functionally equivalent genes thereof considered theoretically potentially relevant for the biologic or pathologic condition(**Feldgajer,** C3:62 through C4:30; ‘A different gene or a different polymorphisms and/or a different mutation and/or a different functionally

equivalent gene thereof of the originally considered genes or polymorphisms and/or mutations and/or functionally equivalent genes' of applicant is equivalent to genetic algorithms which the basic properties are 'mutation, evaluation and selection' of Feldgajer.) training the prediction algorithm with each of the different training sets defined at the previous step for generating a first population of different prediction algorithms which are divided into two groups of mother and father prediction algorithms and testing the prediction algorithms with the associated testing set (**Feldgajer,** C3:62 through C4:30; 'Mother' and 'Father' of applicant would be used in the 'crossover' portion of genetic algorithms of Feldgajer.) calculating a fitness score or prediction accuracy of each father and mother prediction algorithms of the said first population through the testing results (**Feldgajer,** C3:62 through C4:30; 'Calculating a fitness score or prediction accuracy' of applicant is equivalent to 'evaluation' of Feldgajer.); providing an evolutionary algorithm such as a genetic algorithm and applying the evolutionary algorithm to the first population of mother and father prediction algorithms for achieving new generation of prediction algorithms whose training and testing dataset comprises records whose input variables selections are a combination of the input variable selections of the records of the training and of the testing datasets of the first or previous population of father and mother prediction algorithms according to the rules of the evolutionary algorithm (**Feldgajer,** C3:62 through C4:30; "Genetic algorithm' of applicant is equivalent to 'genetic algorithm' of Feldgajer.) for each generation of new prediction algorithms representing each new variant selection of input variables, the best prediction

algorithm according to the best hypothesis of input variable selection being tested or validated through the testing dataset (**Feldgajer,** C3:62 through C4:64; ‘Each generation of new prediction algorithms representing each new variant selection’ of applicant is equivalent to ‘new parameter values are assigned to the plurality of groups’ of Feldgajer.); evaluating a fitness score and the promoting prediction algorithms representing the selections of input variables which have the best testing performance with the minimum number of input variables utilized are for the processing of new generations (**Feldgajer,** C3:62 through C4:64; ‘Fitness score is evaluated’ of applicant is illustrated by finding the ‘best fit’ based on the ‘parameter value’ of Feldgajer.); repeating the preceding two steps until a predetermined fitness score defined as best fit of the prediction algorithm and a minimum number of input variables has been reached (**Feldgajer,** C7:50 through C8:17; ‘Repeating the steps’ of applicant is equivalent to ‘the method is performed iteratively’ of Feldgajer.); and defining as the selected relevant input variables the selected input variables comprising the relevant genes or polymorphisms and/or of mutations and/or of functionally equivalent genes thereof the ones related to the input variables of the selection represented by the prediction algorithm having both at least the predetermined fitness score and also the minimum number of selected input variables. (**Feldgajer,** C7:34 through C8:17; ‘Minimum number of selected input variables’ of applicant is illustrated by a genetic algorithm is used to ‘reduce the amount of information required to generate an adequate result’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify

the teachings of Buscema by using a training set and a testing set and incorporating a genetic algorithm to alter the weights of a neural network as taught by Feldgajer by defining two or more different training datasets each one having records with a set of input variables obtained by excluding one or more input variables from the originally defined number of input variables. while for each record the set of input variables of the corresponding training set has at least one input variable which is not a member of the set of input variables of the other training datasets, each said at least one input variable comprising a different gene or a different polymorphism and/or a different mutation and/or a different functionally equivalent gene thereof of the originally considered genes or polymorphisms and/or mutations and/or functionally equivalent genes thereof considered theoretically potentially relevant for the biologic or pathologic condition training the prediction algorithm with each of the different training sets defined at the previous step for generating a first population of different prediction algorithms which are divided into two groups of mother and father prediction algorithms and testing the prediction algorithms with the associated testing set calculating a fitness score or prediction accuracy of each father and mother prediction algorithms of the said first population through the testing results; providing an evolutionary algorithm such as a genetic algorithm and applying the evolutionary algorithm to the first population of mother and father prediction algorithms for achieving new generation of prediction algorithms whose training and testing dataset comprises records whose input variables selections are a combination of the input variable selections of the records of the training and of

the testing datasets of the first or previous population of father and mother prediction algorithms according to the rules of the evolutionary algorithm for each generation of new prediction algorithms representing each new variant selection of input variables, the best prediction algorithm according to the best hypothesis of input variable selection being tested or validated through the testing dataset; evaluating a fitness score and the promoting prediction algorithms representing the selections of input variables which have the best testing performance with the minimum number of input variables utilized are for the processing of new generations; repeating the preceding two steps until a predetermined fitness score defined as best fit of the prediction algorithm and a minimum number of input variables has been reached; and defining as the selected relevant input variables the selected input variables comprising the relevant genes or polymorphisms and/or of mutations and/or of functionally equivalent genes thereof the ones related to the input variables of the selection represented by the prediction algorithm having both at least the predetermined fitness score and also the minimum number of selected input variables.

For the purpose of using the genetic algorithm to decrease the training time and with the possibility of reducing input parameters.

Claim 31

Buscema does not teach wherein an optimization of the distribution of the records of the original database in a training dataset and in a testing dataset is carried out in one of a pre processing and a post processing phase.

Feldgajer teaches wherein an optimization of the distribution of the records of the original database in a training dataset and in a testing dataset is carried out in one of a pre processing and a post processing phase. (**Feldgajer,** C10:16-26; ‘Optimization of the distribution’ of applicant is equivalent to ‘method using groups’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by optimizing the distribution of records as taught by Feldgajer to have wherein an optimization of the distribution of the records of the original database in a training dataset and in a testing dataset is carried out in one of a pre processing and a post processing phase.

For the purpose of getting a true random sample to reduce training costs.

Claim 32

Buscema teaches defining a set of one or more distributions of the database records onto respective training and testing subsets (**Buscema,** p2, c2:16-34, p4 Figure 4; ‘Training subset’ of applicant is equivalent to ‘training set’ of Buscema. ‘Testing subset’ of applicant is equivalent to ‘testing set’ of Buscema.); using the defined set of distributions to train and test a first generation set of one or more prediction algorithms and assigning a fitness score to each. (**Buscema**, p4 Figure 4; ‘defined set of distributions’ of applicant is illustrated in the ‘training side’ and ‘validation side’ of each ANN of Buscema.)

Buscema does not teach feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation

prediction algorithms and assigns a fitness score to each; and continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equaling or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, and a certain number of generations having been generated.

Feldgajer teaches feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each (**Feldgajer,** C4:43-64; ‘generates a set of one or more second generation prediction algorithms’ of applicant is disclosed by the ‘new parameter values are assigned to the plurality of groups’ of Feldgajer.); and continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs (**Feldgajer,** C3:62 through C4:28; ‘Termination’ of applicant is equivalent to ‘termination condition’ of Feldgajer.) wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equaling or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, and a certain number of generations having been generated. (**Feldgajer,** C2:1-26, C5:63-64, C7:50 through C8:17; ‘Exceeding a defined minimum’ of applicant is disclosed by the neuron and its ‘internal potential limit’ of Feldgajer. This node can be viewed as the output node of the neural network. The node will fire if the .minimum value’ is equaled or exceeded.

‘Converging to a given value’ of applicant is illustrated by the method of employing ‘a convergent result.’ Of Feldgajer. ‘Certain number of generations’ of applicant is equivalent to generation counter’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using a genetic algorithm to alter the weights of a neural network as taught by Feldgajer to have the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each; and continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs wherein said termination event is at least one of a prediction algorithm is generated with a fitness score equaling or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, and a certain number of generations having been generated.

For the purpose of using the genetic algorithm to decrease the training time and with the possibility of reducing input parameters.

Claim 33

Buscema teaches generating a population of prediction algorithm each one of them is trained and tested according to a different distribution of the records of the data set in the complete database onto a training data set and a testing data set. (**Buscema,** p2, c2:16-34, p4 Figure 4; ‘Training subset’ of applicant is equivalent to ‘training set’ of Buscema. ‘Testing subset’ of applicant is equivalent to ‘testing

set' of Buscema. 'Population of prediction algorithm' of applicant is equivalent to 'ANN1 through ANN n' of Buscema.)

Buscema does not teach each different distribution being created by a random distribution or a distribution formed by a pseudo-random distribution

Feldgajer teaches each different distribution being created by a random distribution or a distribution formed by a pseudo-random distribution (**Feldgajer,** p7:50 through C8:17; 'Random or pseudo-random' of applicant is equivalent to 'random or pseudo-random' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using random or pseudo random techniques as taught by Feldgajer to have each different distribution being created by a random distribution or a distribution formed by a pseudo-random distribution

For the purpose of using another method for finding a true random sample.

Buscema teaches each prediction algorithm of the said population being trained according to its own distribution of records of the training set and being validated in a blind way according its own distribution on the testing set (**Buscema**, p4 Figure 4; 'Trained according to its own distribution' and 'validated in a blind way according its own distribution' of applicant is illustrated in the 'training side' and 'validation side' of each ANN of Buscema.)

Buscema does not teach a score reached by each prediction algorithm being calculated in the testing phase representing its fitness; - an evolutionary algorithm being further provided which combines the different models of distribution of

the records of the complete data set in a training and in a testing set which sets are represented each one by a corresponding prediction algorithm trained and tested on the basis of the said training and testing data set according to the fitness score calculated in the previous step for the corresponding prediction algorithm the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value and setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

Feldgajer teaches a score reached by each prediction algorithm being calculated in the testing phase representing its fitness; - an evolutionary algorithm being further provided which combines the different models of distribution of the records of the complete data set in a training and in a testing set which sets are represented each one by a corresponding prediction algorithm trained and tested on the basis of the said training and testing data set according to the fitness score calculated in the previous step for the corresponding prediction algorithm (**Feldgajer,** p4:43-64; 'A score is reached by each prediction algorithm' of applicant by being able to determine which set of parameters provides the 'best

fit' of Feldgajer.) the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets (**Feldgajer,** p4:43-64; 'A fitness score of each prediction algorithm' of applicant by being able to determine which set of parameters provides the 'best fit' of Feldgajer.) repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value (**Feldgajer,** p7:50 through C8:17; 'Repeating the evolution' of applicant is equivalent to 'the method is performed iteratively' of Feldgajer.) and setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm. (**Feldgajer,** p7:50 through C8:17; 'Setting the data records' of applicant is equivalent to 'altering the population or the parameter values' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using fitness scores to determine the standing of a neural network and it's associated values from the genetic algorithm as taught by Feldgajer to have a score reached by each prediction algorithm being calculated in the testing phase representing its fitness; - an evolutionary algorithm being further provided which combines the different models of distribution of the records of the complete data set in a training and in a testing set which sets are represented each

one by a corresponding prediction algorithm trained and tested on the basis of the said training and testing data set according to the fitness score calculated in the previous step for the corresponding prediction algorithm the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value and setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

For the purpose of being able to find the neural network with the best fit to use as a bases for a following iteration.

Claim 34

Buscema does not teach a reduced number of genes, alleles or polymorphisms wherein the reduced number of said genes, alleles or polymorphisms has been selected with a method according to claims 30 to 33.

Feldgajer teaches a reduced number of genes, alleles or polymorphisms wherein the reduced number of said genes, alleles or polymorphisms has been selected with a method according to claims 30 to 33. (**Feldgajer,** C7:34 through

C8:17; ‘Reduced number of genes, alleles or polymorphisms’ of applicant is illustrated by a genetic algorithm is used to ‘reduce the amount of information required to generate an adequate result’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by reducing input values as taught by Feldgajer to have a reduced number of genes, alleles or polymorphisms wherein the reduced number of said genes, alleles or polymorphisms has been selected with a method according to claims 30 to 33.

For the purpose of making the neural network more efficient.

Claim 35

Buscema teaches defining a set of one or more distributions of the database records onto respective training and testing subsets. (**Buscema,** p2, c2:16-34; ‘Training subset’ of applicant is equivalent to ‘training set’ of Buscema. ‘Testing subset’ of applicant is equivalent to ‘testing set’ of Buscema.)

Buscema does not teach using the defined set of distributions to train and test a first generation set of one or more prediction algorithms and assigning a fitness score to each, each of said prediction algorithms being associated with a certain distribution of said records; feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each; continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs, where said termination event is at least one of a

prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, and a certain number of generations having been generated; selecting a prediction algorithm having a best fitness score.

Feldgajer teaches using the defined set of distributions to train and test a first generation set of one or more prediction algorithms and assigning a fitness score to each, each of said prediction algorithms being associated with a certain distribution of said records (**Feldgajer,** abstract, C4:43-64; 'Set of distributions to train and test a first generation set' of applicant is equivalent to 'using genetic algorithms' which generate 'parameter values preferably define a first broad range of values' of Feldgajer. 'Fitness score' of applicant is illustrates by finding output with the 'best fit' of Feldgajer.);feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each(**Feldgajer,** abstract, C4:43-64; 'Feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms' of applicant is disclosed by 'new parameters values are assigned to the plurality of groups' of Feldgajer.); continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs, where said termination event is at least one of a prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value (**Feldgajer,** C2:1-26; 'Exceeding a defined minimum' of applicant is disclosed by

the neuron and its ‘internal potential limit’ of Feldgajer. This node can be viewed as the output node of the neural network. The node will fire if the .minimum value’ is equaled or exceeded.), the maximum fitness score of successive generational sets of prediction algorithms converging to a given value (**Feldgajer,** C5:63-64; ‘Converging to a given value’ of applicant is illustrated by the method of employing ‘a convergent result.’ Of Feldgajer.), and a certain number of generations having been generated (**Feldgajer,** C7:50 through C8:17; ‘Certain number of generations’ of applicant is equivalent to generation counter’ of Feldgajer.); selecting a prediction algorithm having a best fitness score. (**Feldgajer**, C4:43-64; ‘Fitness score’ of applicant is illustrates by finding output with the ‘best fit’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using initial distributions of data with an neural network which results in fitness scores which are then passed into a genetic algorithm for altering the value to improve the fitness level of the neural networks with the next iteration as taught by Feldgajer to have the defined set of distributions to train and test a first generation set of one or more prediction algorithms and assigning a fitness score to each, each of said prediction algorithms being associated with a certain distribution of said records; feeding the set of prediction algorithms to an evolutionary algorithm which generates a set of one or more second generation prediction algorithms and assigns a fitness score to each; continuing to feed each generational set of prediction algorithms to the evolutionary algorithm until a termination event occurs, where said termination event is at

least one of a prediction algorithm is generated with a fitness score equal to or exceeding a defined minimum value, the maximum fitness score of successive generational sets of prediction algorithms converging to a given value, and a certain number of generations having been generated; selecting a prediction algorithm having a best fitness score.

For the purpose of reducing the cost of the training of the neural network.

Buscema teaches using the distribution of database records associated with said selected prediction algorithm in performing supervised learning, said supervised learning including training and testing pf prediction algorithms to obtain a trained prediction algorithm (**Buscema,** p4, Figure 4; 'Using the distribution of database records' of applicant is equivalent to 'Total DB' of Buscema.); and using the trained prediction algorithm to predict the output variables relating to the problem under investigation where only the input variables are known. (**Buscema,** p2:16-39; 'To predict the output variables' of applicant is equivalent to 'classify the new cases' of Buscema.)

Buscema does not teach wherein said method is performed using a computer and computer software forming an intelligent system.

Feldgajer teaches wherein said method is performed using a computer and computer software forming an intelligent system. (**Feldgajer**, C4:43-64; 'Computer and computer software' of applicant is equivalent to 'computer' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using a computer to implement the invention as taught by Feldgajer to have the method

is performed using a computer and computer software forming an intelligent system.

For the purpose of being able to implement the invention with a common machine.

Buscema teaches the method further comprises the steps of generating a population of prediction algorithms, wherein each one of said prediction algorithms is trained and tested according to a different distribution of the records of the data set in the complete database onto a training data set and a testing data set (**Buscema**, p4 Figure 4, p2 C2:16-39; ‘population of prediction algorithms ‘ of applicant is illustrated by ANN1 through ANNn of Buscema. ‘Training data’ of applicant is equivalent to ‘training set’ of Buscema. ‘Tested data set’ of applicant is equivalent to ‘testing set’ of Buscema.)

Buscema does not teach each different distribution being created as one or more of a random distribution or a pseudorandom distribution

Feldgajer teaches each different distribution being created as one or more of a random distribution or a pseudorandom distribution (**Feldgajer,** C7:50 through C8:17; ‘Random’ of applicant is equivalent to ‘random’ of Feldgajer. ‘Pseudorandom’ of applicant is equivalent to ‘pseudorandom’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using random and pseudorandom distributions as taught by Feldgajer to each different distribution being created as one or more of a random distribution or a pseudorandom distribution

For the purpose of getting a true sample for training purposes

Buscema teaches each prediction algorithm of said population is trained according to its own distribution of records of the training set and being validated in a blind way according its own distribution on the testing set. (**Buscema**, p4 Figure 4; 'Trained according to its own distribution' and 'validated in a blind way according its own distribution' of applicant is illustrated in the 'training side' and 'validation side' of each ANN of Buscema.)

Buscema does not teach a score reached by each prediction algorithm is calculated in the testing phase representing its fitness an evolutionary algorithm being.

Feldgajer teaches a score reached by each prediction algorithm is calculated in the testing phase representing its fitness (**Feldgajer,** C4:43-64; If Feldgajer can determine which parameter is the 'best fit' then a 'score' must be generated.) an evolutionary algorithm being (**Feldgajer,** abstract; 'Evolution algorithm' of applicant is equivalent to 'genetic algorithm' of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by using a score to rate performance as taught by Feldgajer to have a score reached by each prediction algorithm is calculated in the testing phase representing its fitness an evolutionary algorithm being.

For the purpose of using the score for future selection.

Buscema teaches further provided which combines the different models of distribution of the records of the complete data set in a training and in a testing

set which sets are represented each one by a corresponding prediction algorithm trained and tested on the basis of the said training and testing data set according to the fitness score calculated in the previous step for the corresponding prediction algorithm (**Buscema**, p4 Figure 4; ‘Training set’ and ‘testing set’ of applicant is equivalent to ‘training’ and ‘validation’ of Buscema. Examiner’s Comment: Feldgajer discloses a method is disclosed that, using genetic algorithms, improves the training characteristics of a neural network. This is used in combination with Buscema that picks both training and testing records from a database. How these training and testing records are picked is disclosed by 'improves the training characteristics of a neural network.')

Buscema does not teach the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

Feldgajer teaches the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the

training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets (**Feldgajer,** C4:43-64; If Feldgajer can determine which parameter is the ‘best fit’ then a ‘score’ must be generated.) repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness value of at least some prediction algorithm related to an associated data records distribution has reached a desired value (**Feldgajer,** C7:50 through C8:17; ‘Repeating the evolution’ of applicant is equivalent to ‘performed iteratively’ of Feldgajer.) setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm. (**Feldgajer,** p7:50 through C8:17; ‘Setting the data records’ of applicant is equivalent to ‘altering the population or the parameter values’ of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by iterating the process between the genetic algorithm and neural networks to modify the neural network as taught by Feldgajer to have the fitness score of each prediction algorithm corresponding to one of the different distributions of the complete data set on the training and the testing data sets being the probability of evolution of each prediction algorithm or of each said distribution of the complete data set on the training and testing data sets repeating the evolution of the prediction algorithm generation for a finite number of generations or till the output of the genetic algorithm converges to a best solution and/or till the fitness

value of at least some prediction algorithm related to an associated data records distribution has reached a desired value setting the data records distribution for the best solution as the optimized training and testing subsets for training and testing prediction algorithm.

For the purpose of lowering the cost of training the neural network.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 10, 14, 21, 22 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema and Feldgajer in view of Lapointe. (U. S. Patent Publication 20030004906, referred to as **Lapointe**)

Claim 10

Buscema and Feldgajer do not teach the steps of said method for optimizing a database of sample records, for selecting the most predictive input variables.

Lapointe teaches the steps of said method for optimizing a database of sample records, for selecting the most predictive input variables. (**Lapointe,** ¶0099; ‘Optimizing a database’ of applicant is achieved by the ‘greedy algorithm’ of Lapointe.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the combined teachings of Buscema and Feldgajer by using the best results as taught by Lapointe to have the steps of said method for optimizing a database of sample records, for selecting the most predictive input variables.

For the purpose of starting the next generation based on the most predictive inputs for efficient training.

Claim 14

Buscema and Feldgajer do not teach wherein the evolutionary algorithm is a genetic algorithm with the following evolutionary rules: an average health value of the population is computed as a function of the fitness values of each single individual in the population; coupling, recombination of genes and mutation of genes are carried out in a differentiated manner depending on the a comparison between the fitness of each individual of the couple and the average health value of the entire population to which the individuals belong; individuals having a fitness value lower or equal to the average health of the entire population are not

excluded from the creation of new generations but are marked out and entered in a vulnerability list; the number of subjects entered in the vulnerability list defining the number of possible marriages.

Lapointe teaches wherein the evolutionary algorithm is a genetic algorithm with the following evolutionary rules: an average health value of the population is computed as a function of the fitness values of each single individual in the population (**Lapointe,** ¶0019; Lapointe invention is in regards to a woman's health.); coupling, recombination of genes and mutation of genes are carried out in a differentiated manner depending on the a comparison between the fitness of each individual of the couple and the average health value of the entire population to which the individuals belong (**Lapointe,** ¶0013 (for 'differentiated manner') and ¶0137; 'Recombination' and 'mutation' of applicant is equivalent to 'genetic algorithms' of Lapointe.); individuals having a fitness value lower or equal to the average health of the entire population are not excluded from the creation of new generations but are marked out and entered in a vulnerability list (**Lapointe,** ¶0430; Since applicant does not exclude the creation that is below a fitness value, this is equivalent to the contingency table of Lapointe. If the information is above a fitness level of applicant then it is on the contingency table of Lapointe. Below a given fitness value would be equivalent to 'vulnerability list.'); the number of subjects entered in the vulnerability list defining the number of possible marriages. (**Lapointe,** ¶0100; Since not all of the population is not involved with marriages then they (vulnerability list) 'defines' the number of possible marriages.) It would have been obvious to a person having ordinary skill in the art

at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by not using individuals which are below the average as taught by Lapointe to have wherein the evolutionary algorithm is a genetic algorithm with the following evolutionary rules: an average health value of the population is computed as a function of the fitness values of each single individual in the population; coupling, recombination of genes and mutation of genes are carried out in a differentiated manner depending on the a comparison between the fitness of each individual of the couple and the average health value of the entire population to which the individuals belong; individuals having a fitness value lower or equal to the average health of the entire population are not excluded from the creation of new generations but are marked out and entered in a vulnerability list; the number of subjects entered in the vulnerability list defining the number of possible marriages.

For the purpose of using individuals with a promising result to be the bases of the next iteration.

Claim 21

Buscema teaches wherein the individuals are the different prediction algorithm representing a corresponding different initial random distribution of data records onto the testing and the training data set and the genes comprise the binary status variable of association of each record to the training and to the testing subset. (**Buscema,** p2, C2:16-34; 'Initial random distribution' of applicant is equivalent to 'random sample' of Buscema.)

Claim 22

Buscema teaches wherein the individuals are the prediction algorithms each one representing a different training and testing data set, the difference residing in a different selection of input variables for each different training and testing subset, and wherein the genes comprise the different selection variable which is provided for each input variable in the different training and testing subsets, the above mentioned selection variable being a parameter indicating the presence/absence of each corresponding input variable in the records of each data set. (**Buscema,** p2, C2:16-34, p4, Figure 4; Buscema discloses different training and validation sets. Figure 4 illustrates both testing and validation have within them ‘present/absent’ categories.)

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 15, 16, 17 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema and Feldgajer as set forth above in view of Boden. (U. S. Patent 5708774, referred to as **Boden**)

Claim 15

Buscema and Feldgajer do not teach wherein for coupling purposes and for generation of children at least one parent individuals must have a fitness value greater than the average health value of the population.

Boden teaches wherein for coupling purposes and for generation of children at least one parent individuals must have a fitness value greater than the average health value of the population. (**Boden,** C6:6-15; 'Average health value' of applicant is equivalent to 'relative fitness' of Boden. Per Boden individuals with a low fitness value may not be selected. Thus, 'Couples with both members that are below the relative fitness level will not be selected.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by having an algorithm for selection as taught by Boden to have wherein for coupling purposes and for generation of children at least one parent individuals must have a fitness value greater than the average health value of the population.

For the purpose of not selecting both pairs that are below the average health value.

Claim 16

Buscema and Feldgajer do not teach wherein each couple of individuals can generate offsprings having a fitness different from the average health, if the fitness of one them, at least is greater than the average fitness, the offsprings of each marriage occupying the places of subjects entered in the vulnerability list which are marked out, so that a weak individual can continue to exist through his own children.

Boden teaches wherein each couple of individuals can generate offsprings having a fitness different from the average health, if the fitness of one them, at least is greater than the average fitness, the offsprings of each marriage occupying the places of subjects entered in the vulnerability list which are marked out, so that a weak individual can continue to exist through his own children. (**Boden,** C6:6-15; If a parent is chosen to have a child then it is due to the fact is a child which has a different fitness value than its parents. If it did not then there would be no improvement within the algorithm.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by choosing one parent above and the second parent below the average health value as taught by Boden to have wherein each couple of individuals can generate offsprings having a fitness different from the average health, if the fitness of one them, at least is greater than the average fitness, the offsprings of each marriage occupying the places of subjects entered in the vulnerability list which are marked out, so that a weak individual can continue to exist through his own children.

For the purpose of allowing the weaker parent to generate offspring that might be above the average health value.

Claim 17

Buscema and Feldgajer do not teach wherein coupling between individuals having a very low fitness value and a very high fitness value are not allowed.

Boden teaches wherein coupling between individuals having a very low fitness value and a very high fitness value are not allowed. (**Boden,** C6:6-15; "Low fitness value' are not chosen to have children.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by not allowing parents that are below the average health value to generate offspring as taught by Boden to have wherein coupling between individuals having a very low fitness value and a very high fitness value are not allowed.

For the purpose of eliminating generations of offspring that will be below the average health value.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 18, 19, 20 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema, Feldgajer and Lapointe as set forth above, in view of Burke and Boden. ('A Genetic Algorithm Tutorial Tool for Numerical Function Optimisation', referred to as **Burke;** U. S. Patent 5708774, **referred to as Boden**)

Claim 18

Buscema, Feldgajer and Lapointe do not teach wherein the following recombination rules of the genes of the parents individuals coupled are considered in the case the parent's individuals have not common genes.

Burke teaches wherein the following recombination rules of the genes of the parents individuals coupled are considered in the case the parents individuals have not common genes. (**Burke,** p29, C2:10-20; 'Not have common genes' of applicant is controlled by Burke's 'Incest laws 0-3'.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema, Feldgajer and Lapointe by considering parents with genes not in common as taught by Burke to have wherein the following recombination rules of the genes of the parents individuals

coupled are considered in the case the parents individuals have not common genes.

For the purpose of starting with a broader domain of genes to avoid a local minimum.

Buscema, Feldgajer do not teach the health of father and mother individuals are greater than the average health of the entire population; the crossover is a classical crossover according to which the genes of the father and of the mother individuals are substituted one with the other starting from a certain crossover point; the health of father and mother individuals are lower than the average health of the entire population; in this case the two children are formed through rejection of the parents genes they will receive by the crossover process.

Lapointe teaches the health of father and mother individuals are greater than the average health of the entire population; the crossover is a classical crossover according to which the genes of the father and of the mother individuals are substituted one with the other starting from a certain crossover point (**Lapointe,** ¶0100); the health of father and mother individuals are lower than the average health of the entire population; in which case the two children are formed through rejection of the parents genes they will receive by the crossover process. (**Lapointe,** ¶0034, ‘Through rejection of the parents genes is equivalent to a ‘sliding window’ or an average of the variable.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the combined teachings of Buscema and Feldgajer by using individuals which are greater than the average as taught by Lapointe to the

health of father and mother individuals are greater than the average health of the entire population; the crossover is a classical crossover according to which the genes of the father and of the mother individuals are substituted one with the other starting from a certain crossover point; the health of father and mother individuals are lower than the average health of the entire population; in which case the two children are formed through rejection of the parents genes they will receive by the crossover process.

For the purpose of using crossover with fit parents for better results.

Buscema, Feldgajer and Lapointe do not teach the health of one of the parents is less than the average health of the entire population while the health of the other parent is greater than the average health of the entire population; in which case only the parents whose health is greater than the average health of the entire population will transmit their genes, while the genes of the parent having an health lower than the average health of the entire population are rejected.

Boden teaches the health of one of the parents is less than the average health of the entire population while the health of the other parent is greater than the average health of the entire population; in which case only the parents whose health is greater than the average health of the entire population will transmit their genes, while the genes of the parent having an health lower than the average health of the entire population are rejected. (**Boden,** C6:6-15; Rejection of the parent which is below the average of applicant is equivalent to 'low fitness value may not be selected' of Boden.) It would have been obvious to a

person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema, Feldgajer and Lapointe by stating the rule where parents with below average health value will not pass on their genes as taught by Boden to have the health of one of the parents is less than the average health of the entire population while the health of the other parent is greater than the average health of the entire population; in which case only the parents whose health is greater than the average health of the entire population will transmit their genes, while the genes of the parent having an health lower than the average health of the entire population are rejected.

For the purpose of following the general guidelines of a genetic algorithm.

Claim 19

Buscema does not teach wherein each gene is characterized by a status level, and wherein genes rejection comprises modifying the status of the genes from one status level to a different status level.

Feldgajer teaches wherein each gene is characterized by a status level, and wherein genes rejection comprises modifying the status of the genes from one status level to a different status level. (**Feldgajer,** C4:28-30; 'Modifying the status' of a gene is accomplished by replacing the worst individuals with the best individuals of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema by changing status levels as taught by Feldgajer to have wherein each

gene is characterized by a status level, and wherein genes rejection comprises modifying the status of the genes from one status level to a different status level.

For the purpose of improving the status for improved results with the next iteration.

Claim 20

Buscema does not teach wherein a modified crossover of the genes of the parents individuals is carried out when the parents individuals has part of the genes that coincide, this modified crossover providing for generating an offspring in which the genes selected for crossover are the most effective ones of the parents.

Feldgajer teaches wherein a modified crossover of the genes of the parents individuals is carried out when the parents individuals has part of the genes that coincide, this modified crossover providing for generating an offspring in which the genes selected for crossover are the most effective ones of the parents. (**Feldgajer,** C3:62 through C4:30; ‘Parents’ of applicant would be used in the ‘crossover’ portion of genetic algorithms of Feldgajer.) It would have been obvious to a person having ordinary skill in the art at the time of applicant’s invention to modify the teachings of Buscema by using better parents, better offspring are created using crossover as taught by Feldgajer to have wherein a modified crossover of the genes of the parents individuals is carried out when the parents individuals has part of the genes that coincide, this modified crossover

providing for generating an offspring in which the genes selected for crossover are the most effective ones of the parents.

For the purpose of improving the status for improved results with the next iteration.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 26, 28 are rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema and Feldgajer as set forth above in view of Rose. (U. S. Patent Publication 20020178132, referred to as **Rose**)

Claim 26

Buscema and Feldgajer do not teach wherein the system is a system for sound or vocal recognition comprising input means responsive to acoustic waves, a processing unit connected to the input means responsive to acoustic

waves, at least a memory in which a software program is stored said program being in the form according to claims 23 or 24 and comprising coded instructions for enabling the processing unit to carry out a method according to claim 1, a further or the same above mentioned memory in which a dataset of known data records is stored or storable and/or input means for storing in the further or the said above mentioned memory a dataset of known data records.

Rose teaches wherein the system is a system for sound or vocal recognition comprising input means responsive to acoustic waves, a processing unit connected to the input means responsive to acoustic waves, at least a memory in which a software program is stored said program being in the form according to claims 23 or 24 and comprising coded instructions for enabling the processing unit to carry out a method according to claim 1, a further or the same above mentioned memory in which a dataset of known data records is stored or storable and/or input means for storing in the further or the said above mentioned memory a dataset of known data records. (**Rose,** ¶0015) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by having data be related to sound or acoustic waves as taught by Rose to have wherein the system is a system for sound or vocal recognition comprising input means responsive to acoustic waves, a processing unit connected to the input means responsive to acoustic waves, at least a memory in which a software program is stored said program being in the form according to claims 23 or 24 and comprising coded instructions for enabling the processing unit to carry out a

method according to claim 1, a further or the same above mentioned memory in which a dataset of known data records is stored or storable and/or input means for storing in the further or the said above mentioned memory a dataset of known data records.

For the purpose of utilizing the invention within a real world environment.

Claim 28

Buscema and Feldgajer do not teach wherein the database of known data records comprises acoustic signals emitted by one or more objects or one or more living beings making part of the typical environment in which the device has to operate or the data relating to one or more images of one or more objects or one or more living beings making part of the typical environment in which the device has to operate to which are univoquely correlated to corresponding known kind, and/or identity and/or meaning of objects to which the acoustic signals or image data are related and/or from which the acoustic signals or image data are generated.

Rose teaches wherein the database of known data records comprises acoustic signals emitted by one or more objects or one or more living beings making part of the typical environment in which the device has to operate or the data relating to one or more images of one or more objects or one or more living beings making part of the typical environment in which the device has to operate to which are univoquely correlated to corresponding known kind, and/or identity and/or meaning of objects to which the acoustic signals or image data are related

and/or from which the acoustic signals or image data are generated. (**Rose, ¶0004**) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by using signals to detect living beings as taught by Rose to have wherein the database of known data records comprises acoustic signals emitted by one or more objects or one or more living beings making part of the typical environment in which the device has to operate or the data relating to one or more images of one or more objects or one or more living beings making part of the typical environment in which the device has to operate to which are univoquely correlated to corresponding known kind, and/or identity and/or meaning of objects to which the acoustic signals or image data are related and/or from which the acoustic signals or image data are generated.

For the purpose of detecting living beings to aid in rendering a decision to an environment.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claim 27 is rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema and Feldgajer as set forth above in view of Breed. (U. S. Patent Publication 20030002690, referred to as **Breed**)

Claim 27

Buscema and Feldgajer do not teach wherein the system is a system for image recognition, the input means being responsive to electromagnetic waves, the system being configured to recognize the shape of an object generating or reflecting electromagnetic waves, and/or the distance and/or the identity of the object.

Breed teaches wherein the system is a system for image recognition, the input means being responsive to electromagnetic waves, the system being configured to recognize the shape of an object generating or reflecting electromagnetic waves, and/or the distance and/or the identity of the object. (**Breed,** abstract) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the combined teachings of Buscema and Feldgajer by using image data I the form of electromagnetic waves as taught by Breed to have wherein the system is a system for image recognition, the input means being responsive to electromagnetic waves, the system being configured to recognize the shape of an object generating or reflecting electromagnetic waves, and/or the distance and/or the identity of the object.

For the purpose of implementing the invention for use for image recognition.

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claim 29 is rejected under 35 U.S.C. 103(a) as being unpatentable over the combination of Buscema, Feldgajer and Breed as set forth above in view of Lapointe. (U. S. Patent Publication 20030004906, referred to as **Lapointe**)

Claim 29

Buscema, Feldgajer and Breed do not teach wherein the system is a specialized system for image pattern recognition having artificial intelligence utilities for analyzing an image in the form of a array of image data records, each image data record being related to a zone or point or unitary area or volume of a two or three dimensional visual image, the said visual image being formed by an

array of the said pixels or voxels and utilities for indicating for each image data record a certain quality among a plurality of known qualifies of the image data records; the system having a processing unit, a memory in which an image pattern recognition algorithm is stored in the form of a software program which can be executed by the processing unit, a memory in which a certain number of predetermined different qualities which the image data records is configured to assume has been stored and which qualities have to be univoquely associated to each of the image data records of an image data array fed to the system, input means for receiving arrays of digital image data records or input means for generating arrays of digital image data records from an existing image and a memory for storing the said digital image data array, output means for indicating for each image data record of the image data array a certain quality chosen by the processing unit in carrying out the image pattern recognition algorithm in the form of the said software program; the image pattern recognition algorithm being a prediction algorithm in the form of a software program, which prediction algorithm is further associated to a system being further provided with a training and testing software program, the system being configured to carry out training and testing according to the method of one or more of the preceding claim; the method being provided in the system in the form of the training and testing software program, and a database being also provided in which data records are contained univoquely associating known image data records of known image data arrays with the corresponding known quality from a certain number of

predetermined different qualities which the image data records is configured to assume.

Lapointe teaches wherein the system is a specialized system for image pattern recognition having artificial intelligence utilities for analyzing (**Lapointe,** ¶0001 and ¶0148; ‘Artificial intelligence’ of applicant is equivalent to ‘neural networks’ of Lapointe.) an image in the form of a array of image data records, each image data record being related to a zone or point or unitary area or volume of a two or three dimensional visual image (**Lapointe,** ¶0148; ‘Pixel or voxel’ of applicant is equivalent to ‘Images are digitized’ of Lapointe.), the said visual image being formed by an array of the said pixels or voxels and utilities for indicating for each image data record a certain quality among a plurality of known qualifies of the image data records (**Lapointe,** ¶0148; ‘Array’ of applicant is equivalent to ‘fixed dimension’ of Lapointe.); the system having a processing unit, a memory in which an image pattern recognition algorithm is stored in the form of a software program which can be executed by the processing unit (**Lapointe,** ¶0006), a memory in which a certain number of predetermined different qualities which the image data records is configured to assume has been stored and which qualities have to be univoquely associated to each of the image data records of an image data array fed to the system (**Lapointe,** ¶0006), input means for receiving arrays of digital image data records or input means for generating arrays of digital image data records from an existing image and a memory for storing the said digital image data array (**Lapointe,** ¶0006), output means for indicating for each image data record of the image data array a certain quality

chosen by the processing unit in carrying out the image pattern recognition algorithm in the form of the said software program (**Lapointe,** ¶0006); the image pattern recognition algorithm being a prediction algorithm in the form of a software program, which prediction algorithm is further associated to a system being further provided with a training and testing software program (**Lapointe,** ¶0066, ¶0010), the system being configured to carry out training and testing according to the method of one or more of the preceding claim; the method being provided in the system in the form of the training and testing software program (**Lapointe,** ¶0010), and a database being also provided in which data records are contained univoquely associating known image data records of known image data arrays with the corresponding known quality from a certain number of predetermined different qualities which the image data records is configured to assume. (**Lapointe,** ¶0006, ¶0148) It would have been obvious to a person having ordinary skill in the art at the time of applicant's invention to modify the teachings of Buscema, Feldgajer and Breed by employing the system for image pattern recognition as taught by Lapointe to have wherein the system is a specialized system for image pattern recognition having artificial intelligence utilities for analyzing an image in the form of a array of image data records, each image data record being related to a zone or point or unitary area or volume of a two or three dimensional visual image, the said visual image being formed by an array of the said pixels or voxels and utilities for indicating for each image data record a certain quality among a plurality of known qualifies of the image data records; the system having a processing unit, a memory in which an image

pattern recognition algorithm is stored in the form of a software program which can be executed by the processing unit, a memory in which a certain number of predetermined different qualities which the image data records is configured to assume has been stored and which qualities have to be univoquely associated to each of the image data records of an image data array fed to the system, input means for receiving arrays of digital image data records or input means for generating arrays of digital image data records from an existing image and a memory for storing the said digital image data array, output means for indicating for each image data record of the image data array a certain quality chosen by the processing unit in carrying out the image pattern recognition algorithm in the form of the said software program; the image pattern recognition algorithm being a prediction algorithm in the form of a software program, which prediction algorithm is further associated to a system being further provided with a training and testing software program, the system being configured to carry out training and testing according to the method of one or more of the preceding claim; the method being provided in the system in the form of the training and testing software program, and a database being also provided in which data records are contained univoquely associating known image data records of known image data arrays with the corresponding known quality from a certain number of predetermined different qualities which the image data records is configured to assume.

For the purpose of using the invention to detect pathological conditions using images wherein the invention is based on neural networks trained using genetic algorithms.

Response to Arguments

6. Applicant's arguments filed on November 18, 2008for claims 1, 3-35 have been fully considered but are not persuasive.

7. In reference to the Applicant's argument:

<u>In the Claims</u>

A. The Rejections under 35 U.S.C. 112, Second Paragraph
Claims 1 and 33 have been rejected under 35 U.S.C. 112, second paragraph because of the term "pseudorandom."

It is respectfully submitted that "pseudorandom" is a term readily recognizable by a person skilled in the art. As evidence, copies are enclosed of Paul E. Black, PSEUDO- RANDOM NUMBER GENERATOR, in Dictionary of Algorithms and Data Structures, National Institute of Standards and Technology; and John Viega, PRACTICAL RANDOM NUMER GENERATION IN SOFTWARE, Virginia Tech.

As additional evidence, also enclosed are pages from six other scientific publications, each identified on the respective page, that use the term "pseudorandom."

Moreover, Feldgajer, US 5,832,466, cited in the Office Action, also uses the term "pseudo-random" without further explanation. See Feldgaier, 8:3.

Based on the foregoing, the rejection under 35 U.S.C. 112, second paragraph is respectfully traversed.

Examiner's response:

The applicant argues that the term 'pseudo random' is a recognizable term within the art. This was not the rejection. The rejection is based on the definition that the term pseudo-random is a relative term. There are terms such as a 'random number generator' and a 'pseudo random number generator.' Some argue there is no true 'random number generators' based on the argument that computer programs run on written code and input. If the code and input can be duplicated then the results of the 'random number generator' can be duplicated and thus are no true 'random' number generators. The Examiner's position is there are 'random number generators' and 'pseudo random number generators.' Neither of these are concrete and additionally the 'pseudo random' is relative. Just how 'random' is the 'pseudorandom distribution' going to be, or just how 'methodical' is the 'pseudorandom distribution' is? The specification is silent on how this is obtained and thus the rejection stands.

8. In reference to the Applicant's argument:

REMARKS

Claims 1 and 3-35 are pending in the application. Because the Advisory Action of October 30, 2008 has informed that the response filed on October 9, 2008 has not been entered, the present amendments to the claims are based on the claim set filed on January 23, 2008.

In the present response, claims 1 and 3-35 have been amended to correct informalities, and claim 35 also has been amended to retain consistency with the recitations of claim 1. Reconsideration and reexamination of the pending claims is respectfully requested in view of the present amendments and remarks.

In the Specification

The Office Action has objected to the specification because some of the references incorporated by reference are not U.S. patents or U.S. patent publications. In order to expedite allowance of the application and without restrictive intent, the incorporation by reference at paragraph [0041] of the specification has been removed.

Examiner's response:

The Examiner notes the amended specification.

9. In reference to the Applicant's argument:

B. The Rejections under 35 U.S.C. 103(a)

Claims 1, 3-9, 11-13, 23-25 and 30-35 have been rejected under 35 U.S.C. 103(a) over Buscema, SCIENTIFIC BACKGROUND OF DYNAMIC ADAPTIVE SYSTEMS ("Buscema I") in view of Feldgajer, US 5,832,466 ("Feldgajer").
Claims 10, 14 and 21-22 have been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Lapointe, US 2003/0004906.
Claims 15-17 have been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Boden, US 5,708,774.
Claims 18-20 have been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Boden and of Burke, A GENETIC ALGORITHM TUTORIAL TOOL FOR NUMERICAL FUNCTION OPTIMISATION.
Claims 26 and 28 have been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Rose, US 2002/0178132.
Claim 27 has been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Breed, US 2003/0002690.
Claim 29 has been rejected under 35 U.S.C. 103(a) over Buscema in view of Feldgajer and further in view of Boden and Lapointe.
The rejections under 35 U.S.C. 103(a) are respectfully traversed at least for the following reasons.

With regard to independent claim 1, Buscema I discloses an artificial neural

network (ANN) as an example of a dynamic adaptive system. Buscema I further discloses that, to provide a supervised teaching and testing of ANNs, the records of a database of known cases are subdivided in training and in testing databases, and that after such distribution is performed, the ANN that provides the best output distribution during testing in relation to known outputs is selected as the best network.

Feldgajer teaches a system and a method for dynamic learning control in genetically enhanced back-propagation neural networks, in which an ANN is designed such that an output response to training is dependent on at least a parameter value of the ANN.

In particular, Feldgajer teaches that, as a first step, an ANN population is generated that includes a plurality of individual ANNs having a known architecture that are divided into groups. Each ANN is provided with a unique parameter value (such as learning rate and momentum), selected to provide genetic diversity among the population. A plurality of input stimuli is then applied to the individuals within the groups, and the "best fit" is determined as the parameter value of the individual that provides a closest output response to the expected output response. New parameter values are subsequently assigned to the groups of individuals based on such "best fit," such that <u>the newly assigned parameter values define a second range of values.</u> Such variations are conducted using a genetic algorithm method. This process is repeated until an individual falls within a predetermined tolerance of the expected output response. See Feldgajer, 4:43-5:51; 6:11-20; 7:50-8:57.

Neither Buscema I nor Feldgajer, alone or in combination, teach or suggest a method, in which the starting database is distributed in testing and training subsets and a first generation of prediction algorithms is tested to provide fitness scores for the prediction algorithms of the first generation; in which this first generation of prediction algorithms is subsequently fed to an evolutionary algorithm and a set of one or more prediction algorithms is generated therefrom and a fitness score is assigned to each; and in which new populations of prediction algorithms are generated thereafter, which are <u>trained and tested according to different distributions of the records in the database.</u>

Examiner's response:

Applicant argues neither Buscema I nor Feldgajer, alone or in combination, teach or suggest a method, in which the starting database is distributed in testing and training subsets ('Starting database' of applicant is

disclosed by ‘the database used to train the network was composed of 699 cases …’ of Buscema. (**Buscema,** C2:16-39) Training was performed with a random sampling of 257 cases and testing was performed with the remaining 442 cases. Pseudo-random can be viewed as both the training and testing data sets all came from the same initial 699 case database.) and a first generation of prediction algorithms is tested to provide fitness scores for the prediction algorithms of the first generation (‘Fitness score’ of applicant is illustrates by finding output with the ‘best fit’ of Feldgajer. (**Feldgajer,** abstract, C4:43-64)) in which this first generation of prediction algorithms is subsequently fed to an evolutionary algorithm and a set of one or more prediction algorithms is generated therefrom (The ‘first generations’ being fed to an ‘evolutionary algorithm’ and a set of one or more prediction algorithms is generated of applicant is disclosed by ‘using genetic algorithms, improves the training characteristics of a neural network of Feldgajer. (**Feldgajer,** abstract)) and a fitness score is assigned to each (‘Fitness score’ of applicant is illustrates by finding output with the ‘best fit’ of Feldgajer. (**Feldgajer,** abstract, C4:43-64)); and in which new populations of prediction algorithms are generated thereafter, which are <u>trained and tested according to different distributions of the records in the database.</u> (Training was performed with a random sampling of 257 cases and testing was performed with the remaining 442 cases. Pseudo-random can be viewed as both the training and testing data sets all came from the same initial 699 case database. (**Buscema,** C2:16-39))

The Examiner combined Feldgajer which used genetic algorithms to improve the training characteristics of a neural network with Buscema which uses random selection of training and testing of the neural networks from a given database.

10. In reference to the Applicant's argument:

Further, neither Buscema I nor Feldgajer, alone or in combination, teach or suggest that an evolutionary algorithm combines the different models of distribution of the records of the complete data set in one or more training and in a testing sets, <u>each represented by corresponding prediction algorithms</u> trained and tested according to the fitness score calculated in the step discussed in the preceding paragraph.

As shown by the foregoing discussion, Feldgajer teaches combining genetic search techniques with connectionist computation by identifying a "best fit" parameter in an ANN and by exporting such "best fit" parameter to the other ANNs of the population.

Contrary to that, Applicant teaches that that children prediction algorithms are based on a new distribution of records onto the testing and training set, and that such distribution is obtained by merging or mutating the distribution of records of the parent algorithms and not by varying a parameter as in Feldgajer. This causes all children prediction algorithms to be structurally the same but genetically different from as their parent algorithms and from one another, because the children prediction algorithms are generated from different parent algorithms, and, therefore, are trained and tested with training and testing data sets that are different from their parents and from other individuals having different parents.

Claims 3-9, 11-13, 23-25 and 30-35 are believed patentable over Buscema and Feldgajer for the same reasons as claim 1 and for the additional limitations contained therein.

Concerning claims 10, 14 and 21-22; 15-17; 18-20; and 26-29, it is believed that Lapointe, Boden, Burke, Rose and Breed fail to fill the deficiencies of Buscema and Feldgajer, rendering these claims also patentable over the cited references.

Examiner's response:

Applicant argues neither Buscema I nor Feldgajer, alone or in combination, teach or suggest that an evolutionary algorithm combines the different models of distribution of the records of the complete data set in one or more training and in a testing sets, <u>each represented by corresponding prediction algorithms</u> trained and tested according to the fitness score calculated in the step discussed in the preceding paragraph. Feldgajer discloses a method is disclosed that, using genetic algorithms, improves the training characteristics of a neural network. This is used in combination with Buscema that picks both training and testing records from a database. How these training and testing records are picked is disclosed by 'improves the training characteristics of a neural network.'

Examination Considerations

11. The claims and only the claims form the metes and bounds of the invention. "Office personnel are to give the claims their broadest reasonable interpretation in light of the supporting disclosure. *In re Morris*, 127 F.3d 1048, 1054-55, 44USPQ2d 1023, 1027-28 (Fed. Cir. 1997). Limitations appearing in the specification but not recited in the claim are not read into the claim. *In re Prater*, 415 F.2d, 1393, 1404-05, 162 USPQ 541, 550-551 (CCPA 1969)" (MPEP p 2100-8, c 2, l 45-48; p 2100-9, c 1, l 1-4). The Examiner has the full latitude to interpret each claim in the broadest reasonable sense. Examiner will reference

prior art using terminology familiar to one of ordinary skill in the art. Such an approach is broad in concept and can be either explicit or implicit in meaning.

12. Examiner's Notes are provided to assist the applicant to better understand the nature of the prior art, application of such prior art and, as appropriate, to further indicate other prior art that maybe applied in other office actions. Such comments are entirely consistent with the intent and sprit of compact prosecution. However, and unless otherwise stated, the Examiner's Notes are not prior art but link to prior art that one of ordinary skill in the art would find inherently appropriate.

13. Examiner's Opinion: Paragraphs 11 and 12 apply. The Examiner has full latitude to interpret each claim in the broadest reasonable sense.

Conclusion

14. The prior art of record and not relied upon is considered pertinent to the applicant's disclosure.

-U. S. Patent Publication 20020090631: Gough

-U. S. Patent Publication 20020016665: Ulyanov

-U. S. Patent 5799301: Castelli

-U. S. Patent 5140530: Guha

15. Claims 1, 3-35 are rejected.

Correspondence Information

16. Any inquiry concerning this information or related to the subject disclosure should be directed to the Examiner Peter Coughlan, whose telephone number is (571) 272-5990. The Examiner can be reached on Monday through Friday from 7:15 a.m. to 3:45 p.m.

If attempts to reach the Examiner by telephone are unsuccessful, the Examiner's supervisor David Vincent can be reached at (571) 272-3080. Any response to this office action should be mailed to:

Commissioner of Patents and Trademarks,

Washington, D. C. 20231;

Hand delivered to:

Receptionist,

Customer Service Window,

Randolph Building,

401 Dulany Street,

Alexandria, Virginia 22313,

(located on the first floor of the south side of the Randolph Building);

or faxed to:

(571) 272-3150 (for formal communications intended for entry.)

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/P. C./

Examiner, Art Unit 2129

Peter Coughlan

12/22/2008

/David R Vincent/

Supervisory Patent Examiner, Art Unit 2129